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Comparing the Forecasts of Money Demand

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Abstract

The demand for money depends positively on the price level and real income, and negatively on nominal interest rates and wealth. In addition, since the amount of wealth in an economy is fixed, an individual's or firm's wealth is typically tied up between money and bonds. When one of these markets is in equilibrium, so is the other and resultantly money supply is equal to money demand at a particular interest rate. The interest rate affects the movement of the money supply, and Federal Reserve Bank policy influences the short-term interest rate. Monetary policy also affects the price level, while real income in turn affects the movement of money demand. The interaction of money supply and demand leads to a series of equilibriums in the money market. This paper is concerned with the forecasting of money demand changes relative to levels and using price level/inflation, real income, wealth, and interest rate as independent variables. Money demand is approximated by the quantity of M2 money stock, and the price level and interest rate are represented by the consumer price index and 3-month Treasury bills respectively. The forecasting tools used are neural networks and robust multiple linear regression. The efficacy and relative accuracy of the forecasts are determined by performance metrics correlation, root mean square error, and visual analysis. As expected, neural networks yielded a better overall forecast of the changes in money demand.

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Keywords: Money; Interest Rate; Real Income; Wealth; Price Level; Inflation; Forecasts; Neural Networks; Regression Analysis

1. Introduction

At its most basic level the behavior of the money stock is described by four endogenous variables. These variables are real income, wealth, inflation, and interest rates [1]. The money stock is important because its changes are directly related to changes in the demand for loanable funds in the economy. Loanable funds are integral to future investment and consumption and their growth, both positive and negative, is a major factor in determining the path an economy will follow. The Federal Reserve (Fed) of the United States uses changes in the money supply to affect loanable funds through direct sales or purchases of government bonds in the open market [2, 3, 4]. The Fed also influences the proportion of the money stock held by the public through changes in short-term interest rates [2,

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3].

The growth of income has a positive relationship to the money supply [5]. As income grows, there is more need and demand for both money and loanable funds. Wealth is also a determinant of the demand for money because of its influence on the composition of portfolios [3]. As wealth in an economy increases, there is increased demand for financial instruments such as stocks and bonds and there is a reduced demand for liquidity. Inflation is also a strong determinant of the money supply, and it is arguably determined by excess money in the economy [5, 6, 7].

The management of the money supply became critical over the 2007-2009 financial crisis, and this study analyzes the behavior of the four fundamental determining variables of the money stock – real income, wealth, inflation, and interest rates – over this period, and seeks to answer the question of the robustness of the forecasts of the changes in the money stock as the unanticipated and major economic and financial upheaval known as the Great Recession developed, progressed and ended.

Of the four variables income, wealth, inflation and interest rate, the Fed only has influence on and primary control over interest rates in the short-run. Thus, the forecasts generated in this study, while also using income, wealth, and inflation as independent variables, can be viewed as a simple test of the influence of changes in interest rates by the Fed in determining the growth path of the money stock and the economy. In this regard, our empirical results are positive, and reveal a high correlation between changes in interest rates and changes in the money stock. The money supply data used is M2 as reported by the St. Louis Federal Reserve Data Bank (FRED); the data used for income is Real Personal Disposable Income as reported by the U.S. Department of Commerce; the inflation indicator is derived from the Consumer Price Index all Items as reported by the U.S. Department of Labor, Bureau of the Census; the wealth data are derived from personal savings as reported by the U.S. Department of Commerce: Bureau of Economic Analysis.

2. Methods and Materials

Economic forecasting is critical to the tactical, operational, and strategic decision making of many business and government organizations, whether it is a business considering future investments in capital goods or a government planning a tax rate increase [8, 9]. Because forecasting is crucial to economic decision making, myriad forecasting methods with the potential to improve the accuracy of economic decisions about future outcomes have been used. Among them are neural networks. Neural network models have been successfully applied to many business areas [9, 10]; a few examples include earnings yield, exchange rates, bankruptcies, stock return, and product and retail sales. Neural networks nonparametric and data driven features as well as their ability to handle complex data sets such as those with inherent nonlinearity and nonstationarity provide a decided advantage over linear forecasting methods when the data of concern are complex. In addition, for time series data, including the gross domestic product, taking the difference and then using neural network models to perform the forecast tend to produce very good results [11]. Moreover, an added complexity to the forecasting of complex data sets involves the forecasting horizon. Also, neural network models have shown some successes in multistep ahead prediction of real data compared to linear models, which have been generally unsuccessful in multistep ahead forecasting [12].

This study mainly pertains to neural network forecasting of changes in money demand. The neural network models were of the focused gamma type with similar setups to those found in Joseph and Larrain [13], except in some of the details, see Table 1. For example, models 2 and 7 of the seven models used the conjugate gradient descent backpropagation through time algorithm for the training under supervised learning. The tap delay equaled one and nine processing elements were used in all of the models. To compare the efficacy and relative accuracy of the forecasted changes of money demand using neural networks, robust multiple linear regression [13] consistent with the general setup of the neural network models where possible and the levels of money demand were used to provide a benchmark for appraising the neural network and multiple linear regression models' performance on out-of-sample data. The setups of the neural network models for forecasting the levels of money demand were similar to the setups for forecasting the changes in money demand. The setups for the robust multiple linear regression were similar to those found in Joseph and Larrain [13], except for the forecasting of the levels of money demand the weighting function used in the regression models was ordinary least squares. Both the levels of and the changes in money demand were found to be predictable with the Hurst exponent exceeding 0.5: 0.8598 and 0.8324 respectively. For the regression models associated with the forecasting of the changes in money demand, the most dominant coefficients were linked to predictor variables inflation, wealth, real income, and interest rate in that consistent order for the seven models, see Table 2. For example, the coefficients for inflation were 0.8293, 0.7888, 0.7090, 0.6863, 0.6501, 0.5841, and 0.5668. The coefficients linked to the predictor variables in the levels forecast were less consistently aligned, see Table 2. Some even had negative signs associated them. The general form of the regression model for target variable money (m) and predictor variables income (y), wealth (w), inflation (i), and interest rate (r) is the following: $m(t) = c_o + c_1 y(t) + c_2 w(t) + c_3 i(t) + c_4 r(t)$.

Table 1. Neural network models' training, testing, and setup for the changes in money demand forecasting

Models	Training						Testing	
	Time Span	No. of Samples	RMSE	Correlation	Taps	Algorithm	Time Span	No. of Samples
Model 1	03/1963-04/1997	410	0.1977	0.9097	7	LM	05/1997-06/2000	38
Model 2	03/1963-06/2000	448	0.1367	0.9459	7	CG	07/2000-08/2003	38
Model 3	03/1963-08/2003	486	0.1871	0.8882	3	LM	09/3003-10/2006	38
Model 4	03/1963-10/2006	524	0.1414	0.9389	3	LM	11/2006-12/2009	38
Model 5	04/1966-12/2009	524	0.1970	0.8823	4	LM	01/2010-05/2011	17
Model 6	10/1967-05/2011	524	0.1470	0.9300	2	LM	06/2011-04/2012	11
Model 7	10/1967-04/2012	535	0.1459	0.9304	3	CG	05/2012-02/2013	10

Note 1: The eight models used to forecast the levels in money demand were similarly trained, tested, and setup.
Note 2: LM is Levenberg-Marquardt; CG is conjugate gradient; tap delay = 1; activation function is tanh; and total processing elements = 9.

Table 2. Coefficients of regression models predictors variables' changes and levels

Models	Regression Coefficients				
	Constant	Income	Wealth	Inflation	Interest Rate
Model 1	-0.1620 (-0.0173)	0.4732 (0.1349)	0.7946 (0.1045)	0.8293 (0.3134)	0.2321 (0.0203)
Model 2	-0.1167 (-0.0361)	0.5587 (0.1618)	0.6499 (-0.0863)	0.7888 (0.3993)	0.2750 (0.0250)
Model 3	-0.0681(-0.0398)	0.5433 (0.1699)	0.5632 (-0.1428)	0.7090 (0.4280)	0.3481 (0.0302)
Model 4	-0.0525 (-0.0313)	0.5057 (0.1636)	0.5362 (-0.0065)	0.6863 (0.3462)	0.3250 (0.0170)
Model 5	-0.0351 (-0.0193)	0.4639 (0.1876)	0.5370 (0.1717)	0.6501 (0.2114)	0.3509 (0.0004)
Model 6	-0.0132 (0.0019)	0.4218 (0.3848)	0.5817 (0.1637)	0.5841 (0.0753)	0.3693 (0.0356)
Model 7	0.0020 (0.0138)	0.4126 (0.6076)	0.5024 (0.1642)	0.5668 (-0.0919)	0.3561 (0.0262)
Model 8	(0.0161)	(0.7625)	(0.0884)	(-0.1491)	(0.0286)

Note: Values enclosed in parenthesis pertain to the coefficients of the predictor variables' levels

The original data sets of real income, wealth (generated from cumulated savings), price (consumer price index), and interest rate (3-month T-bill) started January 1959 and ended February 2013, and totaled 650 samples. The levels of money demand were filtered using Matlab wavelet function *cmddenoise* with Daubechies wavelet db10, and normalized to within ±1 and the interest rate data set was inverted using the additive inverse. The data sets were then setup to provide a 20-month lead of the predictor variables real income, wealth, price, and interest rate over the target money demand for a 20-month ahead prediction, thereby reducing the levels data sets to 630 samples each. The target variable money demand was linearly related to predictor variables real income, wealth, and price; and nonlinearly related to interest rate. To get the changes of the real income, wealth, price, inverted interest rate, and money, their filtered normalized values were subjected to 24-month differencing (relative difference for real income, price, and money and backward first difference for inverted wealth and inverted interest rate). The price variable then became the inflation variable. Money demand was nonlinearly related to income, wealth, inflation, and interest rate. Moreover, with income and interest rate setup to have a 4-month lead on money and inflation and wealth setup to have a 26-month lead on money, the changes data sets were setup for 4-month ahead prediction. The resulting data sets consisted of 600 samples. In both the levels of and changes in money and the predictor variables, the means were removed.

Thirty- six percent (226 samples) of the levels data sets were used for testing and 32% (190 samples) of the changes data sets were used for testing; these data sets were subdivided into smaller data subsets for the respective eight and seven forecasting models. The remaining 64% and 68% of the levels and changes data sets respectively were used accordingly to train the models. The efficacy and relative accuracy of the forecasts during the testing periods were determined using root mean square error (rmse) and correlation (r) error metrics.

3. Results

In examining the relative forecasts of neural network and regression models on the benchmark, levels of money demand, it was found that the neural network models essentially performed as well (correlation metric) or better (rmse metric), see Table 3. The correlation associated with the forecast of the neural network models was 99% of that associated with the forecast of the regression models – 0.9801 and 0.9889 respectively, whereas the rmse associated with the neural network models' forecast was less than half that associated with the regression models' forecast – 0.0580 and 0.1280 respectively. However, there are more instances where regression models individually performed better than the individual neural network models. Three of the eight neural network models (models 1, 7, and 8) produced relatively smaller rmse values (0.0316, 0.1105, and 0.1233 respectively) and two of the eight models (models 5 and 7) produced relatively larger correlation values (0.9921 and 0.8781 respectively), see table 3.

Table 3. Forecasts of money demand levels performance metrics

Performance Metrics		Models								
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Overall
r	NN	0.9041	0.9756	0.9942	0.9821	**0.9921**	0.9504	**0.8781**	0.7856	0.9801
	RR	**0.9073**	**0.9993**	**0.9956**	**0.9935**	0.9876	**0.9866**	-0.0486	**0.9508**	**0.9889**
rmse	NN	**0.0316**	0.1382	0.0954	0.0975	0.1806	0.1510	**0.1105**	**0.1233**	**0.0580**
	RR	0.0476	**0.0119**	**0.0346**	**0.0613**	**0.1098**	**0.1304**	0.1518	0.2720	0.1280

Note: NN is neural network and RR is robust regression

Visually, the neural network models' forecast of the levels of money demand match the actual money demand curve more closely, but the regression forecast appeared to be smoother in the first half of the curve, see Fig 1.

In the forecasting of the changes in money demand, the neural network models out-performed the regression models in producing a better overall aggregate forecast and individual forecasts. In table 4, it is shown that with the aggregate forecasts of neural networks and regression, the neural networks forecast is more than four times larger on the correlation metric (0.8478 compared to 0.1942) and more than three times smaller on the rmse metric. Except for model 3 on the correlation error metric, the individual neural network models produced better forecasts based on both the correlation and rmse error metrics, see Table 4. For example, over the period of the great recession – December 2007 to June 2007 [10, 13], the correlation and rmse associated with neural network and regression models' forecasts were (**0.9337**, 0.9420) and (**0.1619**, 0.1927) respectively. Graphically, the aggregate forecast

Table 4. Forecasts of money demand changes performance metrics

Performance Metrics		Models							
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Overall
r	NN	**0.9328**	**0.8228**	0.8001	**0.9337**	**0.9663**	**0.9881**	**0.8157**	**0.8478**
	RR	0.6952	0.7138	**0.8292**	0.6216	0.9420	0.9439	-0.0518	0.1942
rmse	NN	**0.0843**	**0.0707**	**0.1005**	**0.1619**	**0.0959**	**0.0883**	**0.1616**	**0.1137**
	RR	0.2837	0.3759	0.1310	0.1927	0.2461	0.7453	1.0564	0.3893

Note: NN is neural network and RR is robust regression

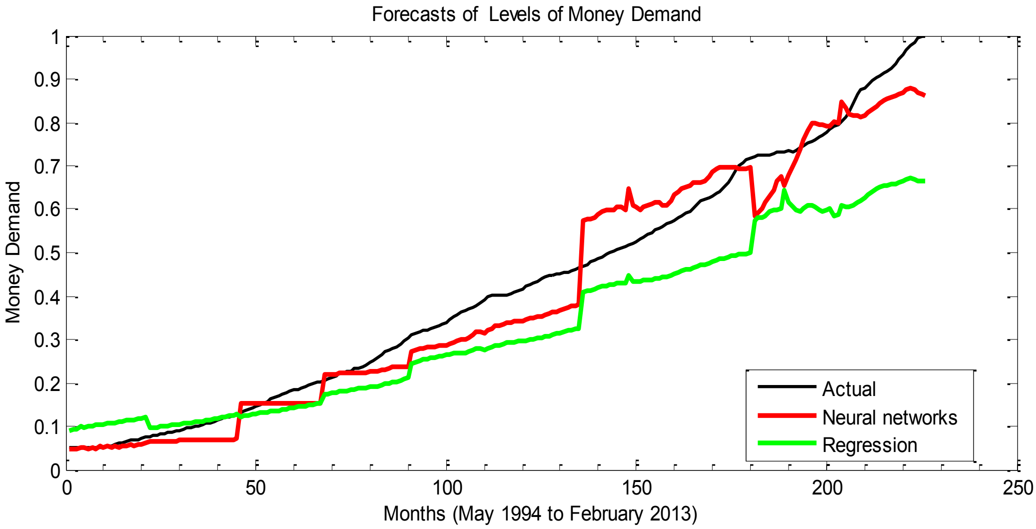

Fig. 1. Forecasted levels of money demand

produced by the neural network models more closely approximate the actual money demand changes, except for minor deviations, see fig. 2.

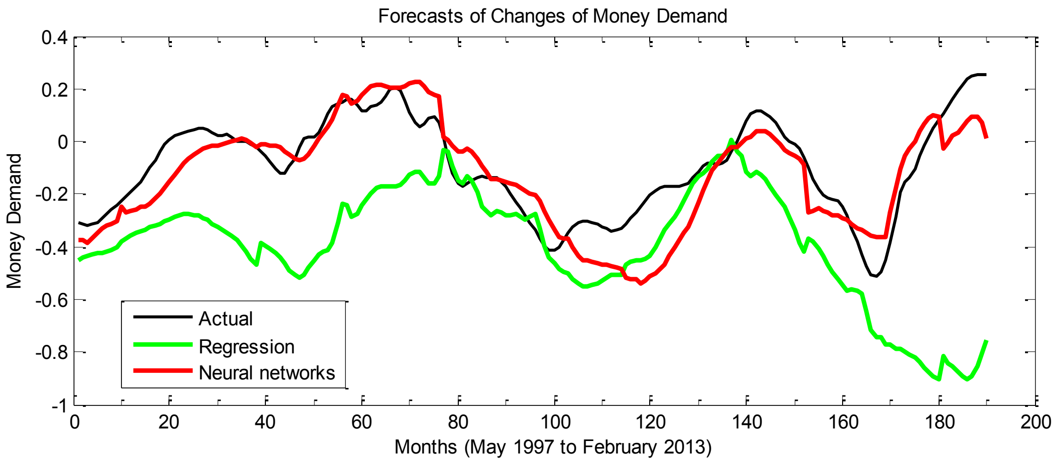

Fig. 2. Forecasted of changes in money demand

4. Discussion

In the benchmark forecasts of the levels of money demand, where real income, wealth, and price were each linearly related to money while interest rate was nonlinearly related to it, one would tend not to be surprised by superior performance of the regression models on the aggregate forecast, but here neural networks performed as well or better. This produced the confidence that the neural network models would out-perform the regression models on the forecasting of changes in money demand since each of real income, wealth, inflation, and interest rate was nonlinearly related to money demand and the known fact that neural networks excellence comes out when the data sets of concern are complex with such properties as nonlinearity and nonstationarity, which are characteristic of the typical economic data of interest [8]. Indeed, the neural network models excelled over the regression models on forecasting the changes in money demand over the 190 samples of the testing period, which started in May 1997 and ended in February 2013.

5. Conclusion

The forecast of changes in the money demand generated by the neural network system is indicative of a successful effort by the Federal Reserve in targeting the money supply over the difficult years covering the period 2007-2010 as it guided the U.S. economy through first an incipient downturn in early 2007, then a major recession over 2008 into 2009, and a recovery starting from mid-2009 through today. Over this period the Fed had strong control and aggressively used short-term interest rate to manage the money supply and the economy. Interest rates are singled out because their impact on the economy is much more immediate than either wealth or inflation. Income is also an important force in shaping money demand, but its effect on the financial markets is far less than its effect on the products markets. The great recession was financial and so was the financial variable wielded by the Fed, the short-term interest rate -- that was the likely force that first arrested and then reversed this major economic downturn. Therefore, the recovery the U.S. economy enjoys today, and probably the fact that the U.S. did not experience a more severe slowdown approaching a depression categorization is very likely attributable primarily to the efforts of the Federal Reserve over this period. Moreover, the overall positive results of this study reveal a strong correlation between changes in interest rates and changes in the money stock. During the contractionary period of the great recession -- December 2007 (sample 128) to June 2009 (sample 146) -- the neural networks' forecast showed very close resemblance and coincidence with the actual money demand. The rise in the changes of the money demand might be indicative of more money in the public and business sectors of the economy. This would naturally motivate the Fed to act prudently to stabilize the economy and economic activities.

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